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A Novel Adaptive Self-turned PID controller based on Recurrent-Wavelet-Neural-Network for PMSM Speed Servo Drive System

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Abstract

The conventional PID controller can not have a satisfactory performance when it has been applied in the permanent-magnet synchronous motor (PMSM) speed regulation system which has the characteristics of nonlinearity, strong coupling and multi-variable. With the purpose to solve this problem, a new hybrid control algorithm utilizing recurrent wavelet neural network (RWNN) is proposed, which can adjust parameters on line to be adaptive to the parameter variety and load disturbance. The effectiveness of the proposed controller is demonstrated by numerical simulations and experiments. It is proved that this scheme not only has good dynamics and steady-state performance but also enhances the robustness of system.

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Recurrent wavelet neural network; PMSM; speed regulation system; field oriented vector control; SVPWM

1. Introduction

For the PMSM speed servo system, the characters of PMSM including nonlinearity, strong coupling, multivariable make it is difficult to apply a normal PID controller to attain a good performance [1-3]. Although some scholars improved PID basing on intelligent control algorithm, these schemes has their own disadvantage and a lot are only in simulation and not implemented in actual system [4-8].

A novel improved PID algorithm based on recurrent wavelet neural network is proposed in this paper, which combines the capability of artificial neural networks for learning from the process and the capability of wavelet decomposition for identification and control of dynamic systems [9-10]. Simulations and experiments have been given to demonstrate that the RWNNPID controller has superiority to normal

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PID in fast response, good stability and insensitivity to the uncertainty such as parameter changing and load disturbances.

2. Design of the proposed controller

2.1. System structure

System structure is illustrated as Fig. 1. ω^* is the command speed input. ω_m is the anticipated speed of the reference model output. Speed error ω_e and its difference are used as the input of the wavelet neural network. The network calculates on line and provides K_p, K_i, K_d parameters of the PID controller, and then control signal is generated from the PID controller to drive the PMSM vector control system. The network parameter can be corrected automatically which enables the system to be adaptive and self-learning. The motor rotor speed has been fed back to the command input and makes it a speed closed loop system.

2.2. Reference model structure

Model reference adaptive control has been proved that could effectively attenuate disturbance to realize optimal system. In this paper, in order to obtain an expected control performance, a reference model has been used to give a reference speed signal which is subtracted by motor rotor speed to produce an error signal for network training so that controller output can follow the speed of an ideal system. First-order inertial system is adopted as the reference model, transfer function of which is defined as

$$W(s) = \frac{\omega_m(s)}{\omega^*(s)} = \frac{1}{T_{ref}s + 1} \tag{1}$$

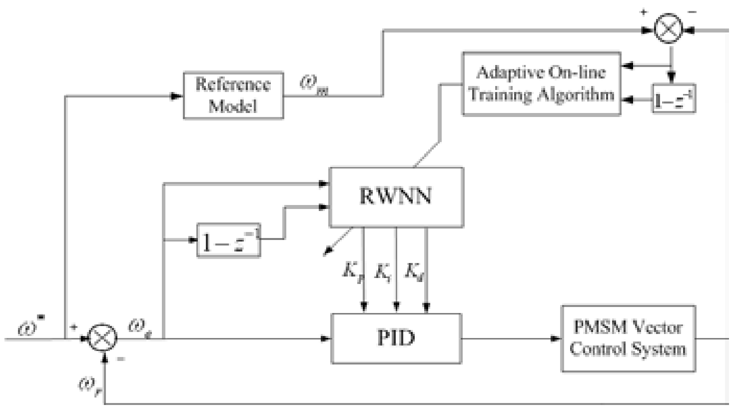

Fig. 1. Recurrent wavelet neural network PID control system

2.3. Design of the current loop

The current close loop of the system can be derived from the PMSM mathematical model [11]. With a PI regulator, the current loop is ultimately simplified to a first-order inertial system, whose transfer function is shown as equation (7)

$$G_i(s) = \frac{1}{(\tau_i / KK_iK_p)s+1} = \frac{1}{T^{'}s+1} \tag{2}$$

where K is scale factor between u_q and i_q , K_i is equivalent small inertia control gain, K_p is current regulator proportional parameter, τ_i is the integral time constant of the current regulator

2.4. Structure of recurrent wavelet neural network

A three layers WNN is used in this design. The input variables of the network are selected as motor speed error and its difference. There are six hidden neuron nodes. The first derivative of the Gaussian function $\phi(x) = -x\exp\left(-x^2/2\right)$ is used as the wavelet function in the hidden layer. Hidden layer has added recurrent nodes' self-feedback to restrain the oscillation by memorizing the old state such that the network could get a stable output. Outputs of network are used for turning PID controller on line to attain good system robust performance.

In order to speed up convergence, Reference [12] is used to initialize the parameters of the RWNN for the proposed controller.

2.5. On-line training algorithm

The parameters of the RWNN need to update by online training for adapting the uncertainty of the control system. In this paper, supervised gradient descent method is chosen as the on line learning algorithm, and the energy function is defined as $E = 0.5e = 0.5\left(\omega^* - \omega_r\right)^2$

Thus, the error term of output layer to be propagated is derived as

$$\delta_k^3 = -\frac{\partial E}{\partial y_k^3} = -\frac{\partial E}{\partial e}\frac{\partial e}{\partial \omega_r}\frac{\partial \omega_r}{\partial y_k^3} \tag{3}$$

The updating terms of each layer weights and translation and dilation parameters can be calculated：

$$\Delta w_{jk}^3 = -\eta_w \frac{\partial E}{\partial w_{jk}^3} = -\eta_w \frac{\partial E}{\partial y_k^3}\frac{\partial y_k^3}{\partial net_k^3}\frac{\partial net_k^3}{\partial w_{jk}^3} = \eta_w \delta_k^3 y_j^2 \tag{4}$$

$$\Delta w_j = -\eta_w \frac{\partial E}{\partial w_j^2} = -\eta_w \frac{\partial E}{\partial y_k^3}\frac{\partial y_k^3}{\partial net_k^3}\frac{\partial net_k^3}{\partial y_j^2}\frac{\partial y_j^2}{\partial net_j^2}\frac{\partial net_j^2}{\partial w_j^2} = \eta_j \delta_k^3 \sum_k w_{jk}^3 y_j^2 \left(N-1\right) \tag{5}$$

$$\Delta \mu_j = -\eta_\mu \frac{\partial E}{\partial \mu_j} = -\eta_\mu \frac{\partial E}{\partial y_k^3}\frac{\partial y_k^3}{\partial net_k^3}\frac{\partial net_k^3}{\partial y_j^2}\frac{\partial y_j^2}{\partial \mu_j} = -\eta_\mu \delta_k^3 \sum_k w_{jk}^3 \phi^{'}\left(net_j^2\right)\frac{1}{\sigma_j} \tag{6}$$

$$\Delta \sigma_j = -\eta_\sigma \frac{\partial E}{\partial \sigma_j} = -\eta_\sigma \frac{\partial E}{\partial y_k^3}\frac{\partial y_k^3}{\partial net_k^3}\frac{\partial net_k^3}{\partial y_j^2}\frac{\partial y_j^2}{\partial \sigma_j} = -\eta_\sigma \delta_k^3 \sum_k w_{jk}^3 \phi^{'}\left(net_j^2\right)\left(net_j^2 - \mu_j\right)\frac{1}{\sigma_j^2} \tag{7}$$

$$\Delta w_{ij}^2 = -\eta_w \frac{\partial E}{\partial y_k^3}\frac{\partial y_k^3}{\partial net_k^3}\frac{\partial net_k^3}{\partial y_j^2}\frac{\partial y_j^2}{\partial net_j^2}\frac{\partial net_j^2}{\partial w_{ij}^2} = \eta_w \delta_k^3 \sum_k w_{jk}^3 \phi'\left(net_j^2\right) x_i^1 \tag{8}$$

where η_w is the learning rate parameter of the connecting weights of the RWNN, η_μ and η_σ are learning rate parameters of translation and dilation parameter.

Accordingly, update law of the parameters of the RWNN are given by

$$w_{jk}^3(N+1) = w_{jk}^3(N) + \Delta w_{jk}^3,\quad w_j^2(N+1) = w_j^2(N) + \Delta w_j^2,\quad w_{ij}^2(N+1) = w_{ij}^2(N) + \Delta w_{ij}^2$$
$$\mu_j(N+1) = \mu_j(N) + \Delta\mu_j,\quad \sigma_j(N+1) = \sigma_j(N) + \Delta\sigma_j \tag{9}$$

It is difficult to get the value of $\partial\omega_r / \partial y_k^3$ in the equation (3) due to the nonlinearity of the PMSM and the uncertainties induced by parameter variations. With a purpose of overcoming this problem and increase the online learning rate of the network parameters, the error term of output layer to be propagated is replaced by $\delta_k^3 = e(k) + e(k)(1 - z^{-1})$ [13-14].

3. Numerical simulations

With the purpose of verifying the feasibility and effectiveness of the control scheme, numerical simulations have been investigated for the normal PID algorithm and proposed control algorithm in the same conditions. The motor parameters used is 200W, 3 poles, 3000rpm, 0.64Nm; rotor moment of inertia is 0.375 $\mathrm{Kg \cdot cm^2}$, rated current is 1.63A, resistance line-line is 8.02 Ω, inductance line-line is 16.3mH, and torque constant is 0.48Nm/A.

The simulation results are shown in Fig. 2. For the proposed controller, speed response is very fast and it is free from any overshoot or undershoot, i.e. has a steady-state zero error and performs a good stability. Load disturbance is also investigated to verify the disturbance rejection capability of the proposed RWNN controller. The results indicate that the RWNN controller is much more insensitive to the disturbance comparing with the conventional PID controller. So it can be conclude from the simulation results that the RWNN PID controller has superior dynamic and steady characteristics and robustness than normal PID controller.

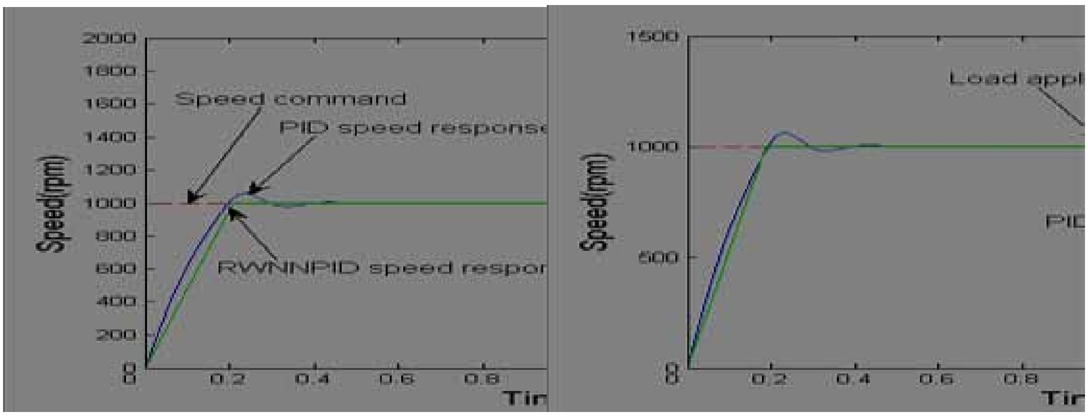

Fig. 2. (a)Simulation investigation of conventional PID and RWNNPID speed response on condition that step speed command is changed; (b) Simulation investigation of conventional PID and RWNNPID speed response on condition that load is applied

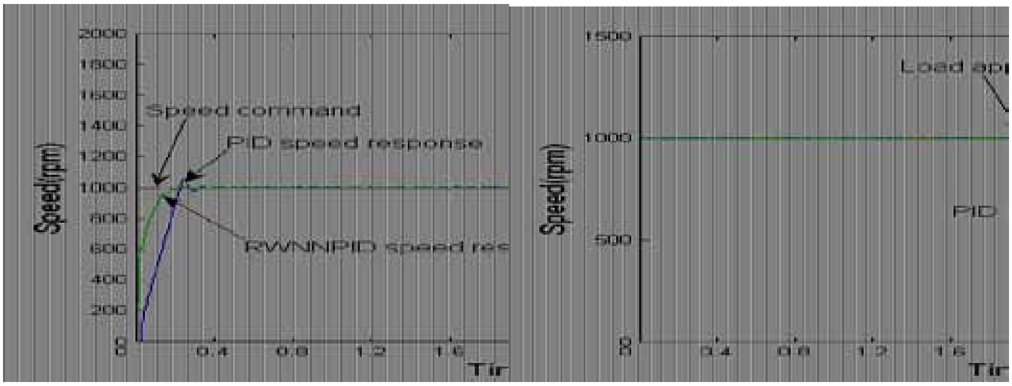

Fig. 3. (a) Experimental results of PID and RWNNPID speed response when step speed command is changed; (b) Experimental results of PID and RWNNPID speed response when load is applied

4. System experiments

To further demonstrate the effectiveness of the proposed controller, a system plat is built and experiments are implemented. In the experiments, a DSP processor TMS320F28335 which is suitable for motor control is chosen to execute algorithm operation. Programs are developed on PC and built into the chip. The control algorithm, coordinate transformation and SVPWM calculation are all realized in the DSP. DSP processor outputs six PWM signals to control IPM to generate three phase signals that are applied to the PMSM. The load changes are carried out by torque controller. The digital incremental encoder mounted on the rotor shaft supplies difference purses which are fed into the QEP module and calculated to get the rotor speed by speed calculating program. Three phase currents are measured by Hall sensors and used for vector control calculation after being converted by A/D module in the DSP. The system sample frequency is 10 kHz, IPM switching frequency is 20 kHz, DC bus voltage is 310V, and resolution of encoder is 2500 P/R.

Experiments are also investigated by comparing RWNN controller and PID controller on conditions of step command and load disturbance, respectively. The experiments results are presented in Fig. 3. From the experiments results, it shows that control system using RWNNPID controller has a smoother running, faster step response and no overshoot or undershoot in comparison with that of using PID controller. Besides, the RWNNPID speed control system wholly has no significant speed change when there is a sudden external load disturbance rather than the PID speed control system presents a evidently speed drop .It indicates the proposed speed controller can effectively decrease the influence of the load disturbance to the system. The experiments results reveal that the RWNNPID speed controller have fast response, good stability and strong disturbance rejection capability, which fully demonstrate the feasibility and effectiveness of the proposed algorithm.

5. Conclusions

PMSM speed control system is a complex system that has the characteristics of nonlinearity, strong coupling and multi-variable. As a result, conventional PID controller is difficult to adjust when it is used in this kind of system. Especially in conditions having rigid requirements, it is difficult to get a flexible, fast and accurate response. In this paper, a new PMSM adaptive PID controller based on RWNN is proposed. This algorithm uses WNN to turn the PID parameters adaptively. The recurrent nodes in addition to the network increase the network response speed and ensure the network has stable outputs. The network training algorithm is working online for obtaining optimal parameters to realize an adaptive system with strong learning ability and good robustness. The proposed algorithm has overcome the problems that conventional PID encounters, and improves the performance in PMSM speed regulation. Furthermore, it creates a new idea to solve control problems of such complex systems. Finally, the experiments present superiorities and verify the feasibility of the proposed algorithm, which can be applied into an actual servo motor speed control system.

Acknowledgements

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